DOCUMENT RESUME

ED 257 212 EA 017 768

AUTHOR Morris, Don R.
TITLE Some Aggregate Characteristics of the Faculties of Elementary Schools Offering Programming Instruction on Microcomputers.
PUB DATE 2 Apr 85
NOTE 23p.; Paper presented at the Annual Meeting of the American Educational Research Association (Chicago, IL, March 31-April 4, 1985).
PUB TYPE Reports - Research/Technical (143) -- Speeches/Conference Papers (150)

EDRS PRICE MF01/PC01 Plus Postage.
DESCRIPTORS *Academic Achievement; Computer Oriented Programs; Elementary Education; *Microcomputers; Programing; *School Statistics; State Surveys; Teacher Background; *Teacher Characteristics
IDENTIFIERS Dade County Public Schools FL

ABSTRACT

Based on responses to a state survey, 173 public elementary schools of Dade County, Florida, were divided into three groups: those who had no instructional microcomputers; those who had them, but did not offer courses in programming; and those who had them and also offered programming. Aggregate measures of faculty characteristics (level of education, salary, ethnic identity) by school were examined with respect to their contribution to student achievement measures. The percent of faculty with higher degrees correlated higher with student achievement in the group of schools offering programming. However, none of the faculty variables was found to make any appreciable contribution to student achievement in any group, independently of more general variables measuring aspects of student ethnicity and community wealth. (Author/TE)

****
* Reproductions supplied by EDRS are the best that can be made *
* from the original document. *
****

ED257212

U.S. DEPARTMENT OF EDUCATION
NATIONAL INSTITUTE OF EDUCATION
EDUCATIONAL RESOURCES INFORMATION
CENTER (ERIC)

This document has been reproduced as received from the person or organization originating it.
Minor changes have been made to improve reproduction quality.

• Points of view or opinions stated in this document do not necessarily represent official NIE position or policy.

"PERMISSION TO REPRODUCE THIS MATERIAL HAS BEEN GRANTED BY

Don R. Morris

TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)."

SOME AGGREGATE CHARACTERISTICS OF THE FACULTIES OF ELEMENTARY SCHOOLS OFFERING PROGRAMMING INSTRUCTION ON MICROCOMPUTERS

Presented by
Don R. Morris

Office of Educational Accountability
Dade County Public Schools

at the
AERA Conference
Chicago, Illinois

April 2, 1985

EA 017 768

Abstract

Based on responses to a state survey, 173 public elementary schools of Dade County, Florida were divided into three groups: those that reported that they had no instructional microcomputers; those that reported that they did, but did not offer courses in programming; and those that had computers and did report that they offered programming. Aggregate measures of faculty characteristics (level of education, salary, ethnic identity) by school were examined with respect to their contribution to student achievement measures, while controlling physically for group. The influence of the percent of faculty with higher degrees, on student achievement was found to be greater in the group of schools offering programming. However, none of the faculty variables were found to make any appreciable contribution to student achievement in any group, independently of more general variables measuring aspects of student ethnicity and community wealth.

SOME AGGREGATE CHARACTERISTICS OF THE FACULTIES OF ELEMENTARY SCHOOLS OFFERING PROGRAMMING INSTRUCTION ON MICROCOMPUTERS

Don R. Morris
Dade County Public Schools

I

It is no longer news that instructional microcomputers are not equitably distributed. In a recent survey of the literature, Sally Banks Zakariya has summed up the findings: "Statistics vary from study to study, but the overall picture is [that] ... Between two-thirds and three-quarters of the richest U.S. schools have at least one microcomputer, but about 60 percent of the poorest schools have none."

Increasingly, as more researchers report their findings, it is becoming clear that the equity question is more complex than simple distribution of hardware. One additional distinction that has emerged lies in the way that wealthy and poor schools use the computers. The Christian Science Monitor has pointed out what many others have begun to note, that "Wealthy schools tend to use computers to teach advanced skills, such as programming. Innercity and rural schools are more likely to simply drill students in the three R's."

It is quite plausible, in fact, to argue that the availability of programming instruction is simply the next logical consequence of wealth, once computers have been acquired. Children from wealthy neighborhoods are likely to be predominantly white, have a better command of the English language, and be better disciplined than their less fortunate peers. These qualities attract better educated, more innovative teachers, who command a higher salary, and are more likely to be white, like their students.

Combined advantages at home and at school result in higher test scores, particularly in subjects that require high and consistent concentration of effort. Now, learning to program a computer is highly correlated with skills of logic and mathematics. And although learning to program is generally thought to improve logical and analytical skills, such skills are often used - formally or not - as prerequisites.* At least this tends to be the pattern in secondary schools, where programming is the preferred way of using the computer.

This seems also to apply at the elementary level. Consider the findings of Elizabeth Badger from the Massachusetts Department of Education's Bureau of Research and Assessment, who surveyed all of that state's school systems. As reported by Zakariya, Badger

---

* Whether learning to program actually improves the student's general learning and thinking abilities is open to question. See for example the study by Gullo and Clements.

found that "At the elementary level, there is a significant difference in the ratio of students per computer, but the real difference is in how those computers are used. In the nine wealthiest systems ... most use LOGO in the lower grades [and] In the nine poorest systems ... six use [the computers] only with special groups of students - and only for remedial drill and practice."

The implication of this reasoning is that the progression from wealth to acquisition of computers to instruction in programming has a strong tendency to be linear. At the least, the best predictors of programming instruction are also those that predict whether a school will have a computer in the first place, and these are all most likely to be general indicators of wealth.

This is presumably not inevitable, of course, but it is the pattern of distribution (both of computers and their instructional use) that will be most likely to occur if the process is left to social and market forces, in the absense of central control and planning by school district administration. In this early phase of "computerization", there is evidence that there has as yet been very little in the way of planning and centralization. Shirley Neill reports the results of a fall, 1982 AASA survey to the effect that only a few districts - with or without computers - had done any systematic planning.

It was from this perspective that the distribution of computers and programming instruction in the Dade County elementary schools was examined. Some 20 variables were selected for trial; they are listed in appendix A, with a description of how they were operationalized where necessary. The unit of analysis is the school. The research presented here is exploratory, seeking to identify variables that reflect differences in three groups of elementary schools: those without computers, those with computers which do not offer programming instruction, and those which do offer programming instruction. All data were taken from sources published by the county, or in one case (the 1983 School Summary Survey), the state of Florida.

II

In the fall of 1982, the 175 elementary schools of the Dade County Public School System reported, collectively, a total of 147 microcomputers, used for instructional purposes. A year later, in October, 1983, they reported 542. This represents an annual increase of 369 percent, more than double the increase of 175.4 percent reported by Hayes (1983) for elementary schools nationwide from 1982 to 1983.

Of the 542 microcomputers reported in 1983, 96 had been purchased and distributed over the preceding three years to 92 schools by the central administration, through its Department of Basic Skills. The rest, 82% of the total reported, were acquired in various ways; through other programs, from PTA and other private

organizations, and so on. Large purchases of computers through the Chapter I program had begun, but as of the October, 1983 survey, Chapter I computers were operational in only 19 schools, and in only 8 schools were Chapter I funds the sole source of computers.

Three groups of schools were identified from the 1983 School Summary Data Survey. Forty-one of 173 elementary schools reported that they had no microcomputers to use for instructional purposes. Of the 132 which reported that they had at least one computer, 44 reported that they offered instruction in programming, while 88 reported that they did not offer such instruction. In a preliminary effort to learn whether these schools were actually very different, depending on which group they were in, data was assembled on the 20 variables mentioned earlier. The resulting group means are given in Table 1, along with descriptive titles and abbreviated labels.

Table 1
Mean Values for Selected Variables
on Three Groups of Elementary Schools

Description	Label	Group Means* a	b	c
Enrollment	ENRL	659.10	677.8	656.57
% faculty black	FBLK	35.90	33.14	29.66
% faculty with higher degree	FEDUC	38.67	42.87	47.57
% faculty hispanic	FHIS	25.00	19.49	14.86
% stds on free/reduced lunch	FRL	64.46	52.98	36.06
Ave. faculty salary	FSAL	20.79	21.46	21.94
% faculty white	FWH	38.86	47.59	55.18
Highest grade served	HGSTGRD	5.60	5.66	5.77
% faculty P.I.P.	INIT	29.63	31.92	36.11
% stds limited Engl	LMTDENG	15.75	12.41	11.15
% staff male	MALE	17.38	19.01	19.14
Relative math achvmt	MATH	0.88	1.00	1.29
Number of computers	NUMCMPR	0.00	4.15	4.36
Relative reading achvmt	READ	0.90	1.02	1.25
% students black	SBLK	38.33	35.80	25.52
% students hispanic	SHIS	45.93	35.87	30.75
Computers per student	STDCMPR	0.00	6.41	7.24
% students white	SWH	15.17	27.20	42.09
Ratio:staff to stds recvg corpl pnshmt	THREAT	48.81	48.83	31.02
Years since 1st cmpr	YRSCMPR	0.00	1.69	2.07

* The groups are schools: a) with no computers; b) with no instruction in programming; c) that offer programming.

There is a predominant pattern in the comparative magnitudes of the means. The increase (or decrease) in the size on the means

across the three groups are in the "correct" direction for 17 of 20 variables. Two are ambiguous (THREAT and MALE), and one (ENRL) is not ordered.

That is to say, the mean of the "b" group (computers but no programming) is most often between the means for the other two. The "progression" from low to high mean scores is always in the direction predicted if the groups are regarded as rank ordered on a dimension of wealth or privilege from low (no computers) to high (instruction in programming). On the basis of these preliminary results, further analysis was undertaken to determine whether these apparant patterns reflected real differences among the groups.

III

Two separate stepwise discriminant analyses were performed on the data, using an SPSS package. The two analyses differed in the number of groups in the analysis; the first (referred to as analysis "A") included all three groups, the other (analysis "B") included only the b and c groups. The analyses also differed in some of the variables entered. Both are summarized in appendix B. The major results have been reported elsewhere (Morris, 1984). Pertinant findings are summarized below.

Each analysis revealed one highly significant discriminant function (a second possible discriminant function in analysis A was not statistically significant). The centroids of the groups on both discriminant functions reflect the same directional alignment (position with respect to each other) as do the means of the variables found in Table 1. For analysis A, the centroids range from -.805 for the a group, through -.071 for the b group, to +.893 for the c group. The centroids for the two groups in the second analysis reflect the same order.

Nine variables were identified in analysis A as contributing to the discriminant function, and five in analysis B (see appendix B). The most influential of the variables contributing to analysis A (FWH, MATH, SWH, FRL) are consistent with - in fact about what one would expect from - the wealth thesis, as are several of the variables with smaller total structure coefficients. The results of the second analysis are similiar.

The indication of significant differences among the groups at this general level serves as justification for a more detailed investigation at a lower level of analysis. Table 2 lists the variables for which the group means proved to differ significantly at the .05 level or better. Two of three 2-group variables and eight of 17 3-group variables did not show significant mean differences. The ten survivors are listed in descending order on the size of the F-ratio of the ANOVA. For the three-group variables, pairs of means were further tested for significant differences using the Scheffe test.

Not unexpectedly, the figures in Table 2 are a good reflection of

the discriminant analysis results (the F-ratios for the univariate ANOVAs usually - though not always - indicate the most effective discriminating variables across the groups). The more important variables using the significance criterion are pretty much what the proponents of the wealth hypothesis would have predicted, with three of the top five (SWH, FWH, FRL) reflecting race and wealth more or less directly, the other two (MATH, READ) reflecting the high achievement that is associated with wealthier schools.*

Table 2
ANOVA and Scheffe Test Results for Selected Variables
on Three Groups of Elementary Schools

Label	Group Means*			F-ratio	p**	Scheffe Results** (p level of mean group differences)		
	a	b	c			a-b	a-c	b-c
FWH	38.86	47.59	55.18	19.89	.000	.004	.000	.003
MATH	.88	1.00	1.29	15.29	.000		.000	.000
SWH	15.17	27.20	42.09	14.25	.000	.040	.000	.003
FRL	64.46	52.98	36.06	12.60	.000		.000	.003
READ	.90	1.02	1.25	9.87	.000		.000	.004
YRSCMPR	-	1.69	2.07	8.52	.000	NA	NA	NA
FEDUC	38.67	42.87	47.57	7.18	.001		.002	
FHIS	25.00	19.49	14.86	5.99	.003		.002	
FSAL	20.79	21.46	21.94	3.51	.032		.048	
INIT	29.63	31.92	36.11	2.97	.054			

* The groups are schools: a) with no computers; b) with no instruction in programming; c) that offer programming.
** Only results significant at the .055 level or beyond are listed.

In addition, and of relevance for this discussion, there is the fact that five - or half - of the "top ten" variables that make up Table 2 are measures of characteristics of the teaching faculties of the three groups of elementary schools. As one follows the changes in the mean values of these five variables across the groups of schools, from group a with no computers to group c, where there are faculty members sufficiently skilled to teach programming in at least some minimal form, the schools' teaching faculties become on the average increasingly higher paid, better educated, and likely to be white. The question is, how are these characteristics - some of which are ascriptive and some of which represent achievement - interrelated, and how are they related to the differences in the three groups of schools?

* Neither READ nor MATH, in either the b or c groups, are correlated with YRSCMPR or NUMCMPR, ending any speculation that the technology itself was already producing achievement gains.

The most powerful faculty variable in the discrimination of groups of schools by computer use is FWH, the percent of faculty white. This is clear from the foregoing summary of previous analyses. FWH is among the top three most powerful discriminators in both discriminant analyses (as determined by magnitude of the total structure coefficients), and it ranks first (by size of F-ratio) among all the variables on results from the univariate ANOVAs. In view of this the basic strategy with respect to the other variables has been to examine their unique contribution to selected "outcome variables" in the presence of FWH, while controlling physically for group.

One way to examine the relationship between ascriptive factors (in this case ethnic origin) and achievement (measured here by INIT and FEDUC) is to examine their effect on average faculty salary (FSAL). There are two patterns of interest involving this variable. First, it increases across the groups (see table 2). Second, it is correlated with faculty ethnicity (FWH, r= .53).* To investigate the reasons for these relationships, consider Table 3, which reports the results of a regression of FSAL on the other four faculty variables.

Table 3

Regression of Average Faculty Salary
on Selected Faculty Variables By Group

Indep. Vars	Group a varnc	F*	p	Group b varnc	F*	p	Group c varnc	F*	p
Total R^2	.81793	40.43	.000	.72985	24.32	.000	.73044	24.39	.000
Unique contributions of each variable:**									
INIT	.19890	39.33	.000	.22127	29.49	.000	.32409	43.28	.000
FEDUC	.12536	24.79	.000	.18590	24.77	.000	.07190	09.60	.004
FWH	.05925	11.72	.002	.02127	02.83	.101	.03762	05.02	.031
FHIS	.00448	00.88	.353	.00069	00.09	.763	.00030	00.04	.843

*Since the group n's are unequal, the degrees of freedom for the F-ratios for all groups are based on the n of the smallest group. This results in a doubly conservative estimate of comparative significance, as the same degrees of freedom were again used to determine the p levels.

**The unique contribution is the difference between the R^2's of the regression equations with and without the variable.

* The correlation is across the whole set of 173 schools. Correlation matrices that include all variables discussed in this paper are included in appendix C.

The salary of a teacher in the Dade system is made up of three components: professional incentive plan salary increments measured by the variable INIT; salary increments paid out for the possession of higher degrees, measured by the variable FEDUC; and years of experience, for which no measure is included in this analysis. If variables measuring all three of these components had been available, then the variance accounted for by regressing FSAL on them would differ from unity only by measurement error.

Examining the R^2 values in the table, it is clear that the four variables do very well at accounting for the variance in FSAL across all the groups. The R^2 for group a, however, is considerably higher than for the other two. It follows from the make-up of the variable described above, that the average years of experience for the teaching faculties of schools in this group is correspondingly lower than in the other groups (i. e. the regression including INIT and FEDUC accounts for more of the total variance). The schools in this group tend to have the highest average poverty levels, and the largest average enrollments of ethnic minorities; the characteristics of the inner-city school. Such schools, for a variety of reasons, have the highest personnel turnovers, and consequently the largest percentages of teachers new to the system. This lack of seniority no doubt goes a long way in accounting for the lower average salary found in the a group.

On the other hand, the influence of FWH on salary, judged by its unique contribution, is slight, as one would expect. The fact that the unique FWH contribution is significant in two of three groups is a reflection of accumulated seniority. Conversely, the absense of any FHIS unique contribution reflects that faculty group's lack of any accumulated seniority.*

At the same time this seniority helps to account for the positive correlation between FWH and FSAL, as do the modest positive correlations between FWH and both INIT and FEDUC. White faculty on the average earn more because they have more seniority, are better educated, and are more likely to participate in PIP activities. Thus, although such inferences from aggregate data are subject to question, it is reasonable to conclude that the

---

* It is widely known that the South Florida area has undergone some rather striking population shifts in the past two decades or so. One result of those shifts has been a drop in the percentage of white, non-hispanic students in the Dade County public schools from a majority to just under 28 percent. At the same time the number of hispanic students has increased to 40 percent, with the black enrollment remaining steady at a third. The makeup of the teaching faculty has changed more slowly. In 1983-84, the year in which the data reported here was collected, 50 percent of the public school teachers were white, only 18 percent hispanic. Although no data on years of experience were collected, it is a reasonable inference that the white teachers as a group have considerable seniority, the hispanics very little.

FSAL increase from group a to group c is a reflection of the much more pronounced increase in FWH.

* * *

If the influence of the variables INIT and FEDUC on FSAL indicate that monetary remuneration is achievement based, the impact on the two available student achievement measures is somewhat different. MATH and READ, school level variables that measure a school's gain relative to the district average, both show mean increases from group a to group c. MATH and READ were among the variables identified in the discriminant analyses. Table 4 shows a two-part presentation of the regression of these two variables on the four faculty variables (FSAL is not included).

Table 4

Regression of Student Achievement Variables
on Selected Faculty Variables By Group

	Group a			Group b			Group c		
Variables	b*	t	p	b*	t	p	b*	t	p
MATH on:									
INIT	6.5	2.06	.023						
FEDUC							7.0	2.13	.020
FWH	15.5	4.25	.000	24.3	10.54	.000	17.4	4.85	.000
FHIS	9.3	3.15	.002	13.9	7.14	.000	14.3	3.19	.001
R^2**	.562	11.66	.000	.505	09.22	.000	.503	09.11	.000
READ on:									
INIT	10.5	3.55	.001						
FEDUC				8.1	3.74	.000	6.0	1.94	.030
FWH	12.2	3.59	.001	19.5	8.82	.000	16.4	4.89	.000
FHIS	5.2	2 24	.016	7.6	4.09	.000			
R^2**	.484	08.46	.000	.452	07.45	.000	.416	06.44	.001

* All b's multiplied by 1000 for easier reading. Since the main interest here is comparison across the groups, unstandardized regressions weights are reported. Comparison across variables is not a problem either, since all independent variables involved are computed as percentages. To further facilitate comparison, all t-ratios, F-ratios and resulting p values are computed at df for the group with the lowest n, and results with $p<.05$ omitted.
** F-ratios are given for the R^2 values.

Taken together, INIT and FEDUC do exhibit a pattern across the groups. Looking first at INIT, significant b-weights in group a indicate that that variable contributes significantly to the regression after the other variables are taken into account, for

both dependent variables, with respect to that group. On the other hand, FEDUC's significant contributions are in group c, and (for READ) group b. . .the computer groups. The implication - that the formal education of higher degrees is associated with student achievement in schools with computers, and conversely that the briefer and less formal training represented by INIT is more likely to be influential in schools without computers - is certainly appealing, and plausible.

However, both regressions are dominated by the ethnic variables, FWH and FHIS. Relatively speaking the b-weights are much greater for these variables, and with one exception their effects are significant across all the groups. In particular, the relationship with student achievement is dominated by FWH. The b's are much larger than those for the other variables, without exception, particularly for READ. In addition, this is reinforced by the fact that the unique contributions of FWH (not shown) to the variance accounted for (R-squared) for each dependent variable for each group is overwhelming, accounting for from 34 to 64 percent of the total variance of the regression for MATH, and 21 to 52 percent in the READ regressions. Consequently, since all groups are similarly affected by the ethnicity factor, it follows that schools with greater FWH percentages will tend to have higher MATH and READ averages. Faculty ethnicity has a greater impact than faculty education on student achievement, and FWH is more strongly associated with group c (programming).

Before reaching any final conclusions about the influence of faculty ethnicity on student achievement, however, there are some other factors that merit examination. There is first of all the fact that the distribution of faculty by ethnicity is closely tied to the distribution of students by ethnicity. It was shown in Table 1 that faculty and students of the same ethnic background have the same pattern of mean percentage change across the groups. Both FWH and SWH increase from group a thru group c, while FHIS and SHIS decrease together.*

These patterns are not independent of each other. Table 5 shows the correlations between the faculty ethnic percentages and their corresponding student ethnic percentages; for each of the three ethnic groups, faculty and student percentages are substantially correlated. All are positive and of similar magnitude. Where the students of an ethnic group are, the faculty of that ethnic group tends to be found.

This relationship (between faculty and students of the same ethnic group) suggests a more complex causal chain. Among the

---

* The black groups, FBLK and SBLK, appear to exhibit the same pattern, but the differences are less pronounced. The ANOVA results are not significant in either case. This is no doubt the result of desegregation efforts , and of a minimum hiring quota for FBLK (24 percent in the elementary schools) called controlled staffing. There is no such restriction for the other groups.

Table 5

Correlations Between Average Percent Faculty By Ethnic Type, and Corresponding Average Student Percent of Same Ethnic Type

	White, non-hisp.	Black, non-hisp.	Hispanic
Group a	.6520	.8795	.6787
Group b	.7348	.8343	.8534
Group c	.7721	.8124	.8370

top four variables listed in Table 2 (along with FWH and MATH) is FWH's compliment SWH, and another powerful discriminator of the computer groups, FRL (the percent of students receiving free or reduced-price lunch). Table 6 shows the results of the regression of the student achievement variables MATH and READ on these variables, with FWH included. This collection of independent variables constitutes a better set of predictors than the set reported in Table 4, with R-squared values substantially higher.

Table 6

Regression of Student Achievement Variables on Selected Socio-economic Variables By Group*

	Group a			Group b			Group c		
Variables	b	t	p	b	t	p	b	t	p
MATH on:									
SWH				3.8	2.00	.027			
FRL	-10.9	-4.94	.000	- 9.9	-6.88	.000	-11.4	-4.24	.000
FWH									
R^2	.714	22.48	.000	.822	41.78	.000	.651	16.83	.000
READ on:									
SWH	8.6	2.54	.008	8.3	4.55	.000	6.0	2.20	.017
FRL	- 8.3	-3.96	.000	- 5.7	-4.15	.000	- 5.7	-1.92	.031
FWH	- 4.3	-1.92	.031						
R^2	.674	18.66	.000	.741	25.76	.000	.578	12.34	.000

* See notes for Table 4.

The important point here, however, is the behavior of the variable FWH in the presence of SWH and FRL. With these two variables controlled, the effect of FWH is not significant (that is, the regression weight does not differ from zero) in five of

six instances. In fact, FRL, with regression weights far larger than either of the other two variables, completely dominates the MATH equation, independently of ethnicity. For READ, SWH and FRL contribute about equally to the regression, with FWH making a significant contribution only in group a, the group of schools having no computers. Even there, the b-weight is half the size of that of either other variable.*

V

Five faculty variables differed significantly in mean value on three groups of schools which were distinguished in terms of whether they had instructional computers and how they were used. It seemed reasonable to think that four of these variables might contribute to an understanding of how faculty characteristics combined differently in their contribution to student achievement given differing conditions of instructional technology (i.e. the presence and instructional use of microcomputers). A fifth variable, average salary, was simply a linear combination of two others and a third (years of teaching experience) not included in the study.

It was plausible to think that the influence (on student achievement) of the quantity and quality of teacher education would change from a predominance of in-service and course-work activities (INIT) to a predominance of faculty with higher degrees (FEDUC), as one moved from the group with no computers to the group where programming is offered. That is to say, it seemed reasonable to assume that the acquision of computers, and the subsequent decision to offer classes in programming using them, was in good part a function of a better trained, more assertive faculty. It seemed further that this more capable, active faculty would be a major factor in the fact that student achievement scores (in reading and math) were found to be on the average higher in schools with computers, and higher still with programming instruction.

To some degree this seems to have been the case. There was indeed a difference in the relative influence of INIT and FEDUC in the explanation of both READ and MATH (that is, in the variance explained), with INIT making the significant contribution in group a, and FEDUC making the significant contribution most clearly in group c.

It also seemed plausible to infer that the known influence of the percent of white faculty (FWH) was to a great extent a reflection of higher education and skills; that for historical reasons many of the more active and more assertive faculty happened to be of that ethnic group at this point in time. However, this conjecture was not supported by the analysis. A large effect of

---

* It might be noted that when the variable YRSCMPR (years since acquiring first computer) is added to the regressions for groups b and c (the variance is zero for group a) it makes no significant contribution.

FWH in MATH and READ was found across all groups, independent of INIT and FEDUC, and much greater than the effects referred to above.

Finally, it seemed plausible to expect that at least FWH - the one faculty variable that had consistently been found to be a powerful discriminator in the groups of schools by computer use, and which was highly correlated with MATH and READ - would show some substantial influence on student achievement independently of variables external to the educational system. This supposition too failed to be supported by the findings. When the effect of FWH on student achievement was examined in the presence of SWH and FRL - perhaps the two best indicators of privilege and wealth - the contribution of FWH to either MATH or READ was reduced to insignificance.

In conclusion, then, it would seem that the elementary school faculties - at least as measured by the variables considered here - are not among the major factors in accounting for the increases in student achievement that are reflected in the group of schools that have acquired instructional microcomputers, and in the group that then proceeded to offer instruction in programming. Rather, these faculties appear as intermediaries in a chain of events whereby external socioeconomic forces shape the outcomes of the educational system.

It is important to remember that this data was collected in a large, diverse system with schools representing a wide range of wealth and poverty under conditions where the introduction of computers for instruction was very recent, and where there was little or no opportunity for control by school district authorities over their aquisition, over their distribution (location within the system), or over the instructional uses to which they were put.* The results of this study would seem to be an indication of what happens to the deployment of a new technology, and to the curriculum which it inspires, in the earliest phase of its introduction, prior to the introduction of comprehensive central planning and supervision.

There is however, a complicating factor. Planning and central direction are tending to reinforce the restriction of programming to the more affluent schools, as programs such as Chopter I tend to concentrate their efforts in poorer schools, and also restrict the use of computers purchased with their funds to remedial exercizes for low achieving students. Whether this is wise policy will depend on what further research turns up about the contribution of programming - or the lack of it - to learning and thinking.

---

* This is not to imply that every possible effort was not made to prepare for microcomputer acquisition and instruction. A "Preliminary Plan of Action" in computer education was published by DCPS' Bureau of Education in May, 1981, the product of months of effort. This was followed in October, 1982 by an extensive Computer Education Curriculum Guide.

SOURCES CONSULTED

Aeppel, T. (1982, October 26). Computers no longer just for rich suburban schools. Christian Science Monitor, pp. 1,8.

Becker, H. J. (1982). Microcomputers in the classroom - dreams and realities. (Report No. 319). Baltimore, MD: The Johns Hopkins University, Center for Social Organization of Schools.

Bureau of Education. (1981, May). Computer education: A preliminary plan of action. Miami, FL: Dade County Public Schools.

Center for Social Organization of Schools. (1983, April - 1984, November). School uses of microcomputers. (Six reports, Nos. 1-6). Baltimore, MD: The Johns Hopkins University.

Department of Basic Skills. (1982, October). Computer education curriculum guide. Miami, FL: Dade County Public Schools.

Florida Department of Education. (1983). [School summary data survey, returns for Dade County]. Unpublished raw data processed locally.

Gallo, D. F. & Clements, D. H. (1984). The effects of kindergarten schedule on achievement, classroom behavior, and attendance. Journal of Educational Psychology, 78, 51-56.

Hayes, J. (1984). Microcomputers in the public schools. Spectrum, 2, 14.

Hayes, J. (1983). School districts using microcomputers: A national survey. Spectrum, 1, 33-37.

Morris, D. R. (1984, November). Some aggregate characteristics of elementary schools offering programming instruction. In A. Wardell (Chair), untitled paper session conducted at the Florida Educational Research Association, Orlando.

National Center for Education Statistics. (1982, September 7). Instructional use of computers in public schools. (NCES 82-245). Washington, D.C.: U. S. Department of Education.

Neill, S. B. (1984). High tech for schools: Problems and solutions. Arlington, VA: American Association of School Administrators.

Office of Educational Accountability. (1984, October). Evaluation of the 1983-84 ECIA chapter II computer education project. Miami, FL: Dade County Public Schools.

Office of Educational Accountability. (1984, January). District and school profiles 1983-84. Miami, FL: Dade County Public Schools.

Office of Educational Accountability. (1984, December). Evaluation of the 1982-83 ECIA chapter II computer education project. Miami, FL: Dade County Public Schools.

Zakariya, S. B. (1984, March). The rich get computers: The poor get poorer. American School Board Journal, pp. 29-32, 54.

APPENDIX A
LIST OF VARIABLES

The variables referred to in this paper are listed and described below. They have been grouped into three categories: socio-economic variables, school level variables (both student achievement and physical plant characteristics), and faculty characteristics.

The socio-economic characteristics are those of the student body, by school. They are:

1. SWH, the percent of students who are white, non-hispanic.
2. SBLK, the percent of students who are black, non-hispanic.
3. SHIS, the percent of students who are hispanic.
4. LMTDENG, the percent of students with limited English proficiency.
5. FRL, the percent of students receiving free or reduced-price lunch. This is used as a measure of poverty.

The small number of students not falling into one of the above three ethnic categories were ignored.

The school level variables are as follows:

6. MATH, relative math achievement, is the ratio of median percentile for the highest grade in the school on the 1983 Stanford Achievement Test for mathematics concepts, to the median percentile for that grade in the District.
7. READ, relative reading achievement, is the ratio for the Stanford on reading comprehension, computed as described in number 6 above.
8. HGSTGRD, highest grade served - the highest grade taught in the school.
9. ENRL, enrollment, is the total student membership by school for 1982-83.
10. THREAT, the ratio of staff to students receiving corporal punishment in 1982-83 x 100. This is intended as a measure of the magnitude of the discipline problem. Staff is taken as the full-time staff at the school.

In addition, three other school level variables were used to examine the differences between the two groups which had computers:

11. NUMCMPR, the number of computers, as reported in the summary data survey.
12. CMPRSTDT, computers per student, the number of computers divided by enrollment x 1000.
13. YRSCMPR, years since first computer, is actually the number of years (beginning in 1981) since the school first reported having a computer, in the school summary survey. The range of responses is 0 to 3.

Finally, a number of variables were assembled on the characteristics of faculty and staff:

14. FWH, the percent of faculty white.
15. FBLK, the percent of faculty black.
16. FHIS, the percent of faculty hispanic.

17. MALE, the percent of full-time staff male.
18. FEDUC, the percent of faculty with a higher degree.
19. FSAL, the average faculty salary, in thousands.
20. INIT, the percent of faculty participating in the Professional Incentive Plan (PIP), computed as the dollar amount of the PIP increment divided by the combined total of classroom and exceptional education teachers, and counselors. Such increments can be earned by completing a specified number of class credits and/or inservice points beyond the bachelors degree, and again beyond the masters.

APPENDIX B
SUMMARY OF DISCRIMINANT ANALYSES

Two separate stepwise discriminant analyses were performed on the data described in appendix A, in the context of an earlier analysis. Fifteen of the twenty variables were common to both, and entered in the same manner for both. The three computer information variables were not used in the analysis which included the no-computers group, since the variance for those variables for that group is zero. For students and faculty, only two of the three ethnic percent variables could be run at any one time. White and hispanic were the ones used in the runs reported.

The two analyses also differed in the number of groups in the analysis. The first (referred to as analysis "A") included all three groups. The other (analysis "B") included only the b and c groups.

Stepwise procedures were applied by levels, with the socio-economic variables being entered first, the school level variables next, and then the faculty variables. In the one analysis where they were used, the computer information variables were entered with the school level variables.

A: Discriminant Function Analysis - Three Groups

Discriminating Variable	Total Structure Coefficient*	F for Unique Contribution**	Tolerance after Last Step***
FWH	.78685	2.157	.393
MATH	.73109	4.411	.159
SWH	.72078	.134	.191
FRL	- .67700	.048	.167
READ	.59520	.727	.232
FSAL	.52254	1.022	.599
SHIS	- .35278	6.406	.282
LMTDENG	- .26531	2.767	.315
ENRL	- .03454	1.545	.843

Canonical Correlation = .5173711
Grouped cases correctly classified: 57.23%, tau = .31064
Group centroids: a= - .80569 b= - .07106 c= .89287

APPENDIX B, CONTINUED

B: Discriminant Function Analysis for Two Groups

Discriminating Variable	Total Structure Coefficient*	F for Unique Contribution**	Tolerance after Last Step***
MATH	.74406	7.349	.230
FRL	- .63840	1.158	.201
FWH	.55302	1.025	.576
YRSCMPR	.52857	9.852	.898
STDCMPR	.15011	2.612	.904

Canonical Correlation = .7856327
Grouped cases correctly classified: 74.24%, tau = .40659
Group centroids: b= - .36656 c= .73311

* The product-moment correlation between the variable and the discriminant function.

** This is the F-to-remove statistic after the last variable has been entered in the stepwise procedure.

*** The tolerance is one minus the squared multiple correlation between the variable and the other variables entered, computed after the last step.

APPENDIX C
CORRELATION MATRICES

ALL SCHOOLS 173 CASES

	FSAL	READ	MATH	INIT	FEDUC
FSAL	1.0000				
READ	0.5446	1.0000			
MATH	0.5701	0.8633	1.0000		
INIT	0.6135	0.3766	0.3819	1.0000	
FEDUC	0.7413	0.4635	0.4581	0.2852	1.0000
FWH	0.5372	0.5928	0.5996	0.2555	0.4084
FHIS	-0.1391	-0.1445	-0.0501	0.0464	-0.1194
FRL	-0.6243	-0.8083	-0.8825	-0.4010	-0.4606
SWH	0.5710	0.7978	0.7635	0.3101	0.4900

	FWH	FHIS	FRL	SWH
FSAL				
READ				
MATH				
INIT				
FEDUC				
FWH	1.0000			
FHIS	-0.6053	1.0000		
FRL	-0.6627	0.1143	1.0000	
SWH	0.7653	-0.3501	-0.8235	1.0000

GROUP A 41 CASES

	FSAL	READ	MATH	INIT	FEDUC
FSAL	1.0000				
READ	0.5210	1.0000			
MATH	0.6139	0.8364	1.0000		
INIT	0.6757	0.5811	0.5443	1.0000	
FEDUC	0.7401	0.3918	0.4154	0.3338	1.0000
FWH	0.5391	0.4277	0.4920	0.2287	0.3511
FHIS	0.0696	0.1873	0.2434	0.2939	-0.0193
FRL	-0.6803	-0.7844	-0.8438	-0.5697	-0.4523
SWH	0.5234	0.7255	0.6423	0.3691	0.4243

	FWH	FHIS	FRL	SWH
FSAL				
READ				
MATH				
INIT				
FEDUC				
FWH	1.0000			
FHIS	-0.4122	1.0000		
FRL	-0.5405	-0.2510	1.0000	
SWH	0.6520	-0.0420	-0.7347	1.0000

APPENDIX C, CONTINUED

GROUP B 88 CASES

	FSAL	READ	MATH	INIT	FEDUC
FSAL	1.0000				
READ	0.5177	1.0000			
MATH	0.5195	0.8694	1.0000		
INIT	0.5839	0.2285	0.2234	1.0000	
FEDUC	0.7035	0.4645	0.4034	0.2046	1.0000
FWH	0.4400	0.5652	0.5414	0.1106	0.3645
FHIS	-0.0898	-0.1533	-0.0225	0.0848	-0.0351
FRL	-0.5666	-0.8163	-0.8989	-0.2832	-0.3894
SWH	0.5133	0.8258	0.8017	0.1933	0.4645

	FWH	FHIS	FRL	SWH
FSAL				
READ				
MATH				
INIT				
FEDUC				
FWH	1.0000			
FHIS	-0.6617	1.0000		
FRL	-0.6051	0.1159	1.0000	
SWH	0.7348	-0.3367	-0.8285	1.0000

GROUP C 44 CASES

	FSAL	READ	MATH	INIT	FEDUC
FSAL	1.0000				
READ	0.4780	1.0000			
MATH	0.4700	0.8059	1.0000		
INIT	0.5239	0.3126	0.3834	1.0000	
FEDUC	0.7364	0.3529	0.3871	0.2288	1.0000
FWH	0.5308	0.6045	0.5570	0.3707	0.2763
FHIS	-0.3019	-0.2424	-0.0195	-0.1945	-0.1553
FRL	-0.5455	-0.7106	-0.8071	-0.3262	-0.3982
SWH	0.6160	0.7319	0.6510	0.3441	0.4289

	FWH	FHIS	FRL	SWH
FSAL				
READ				
MATH				
INIT				
FEDUC				
FWH	1.0000			
FHIS	-0.5343	1.0000		
FRL	-0.6985	0.1796	1.0000	
SWH	0.7721	-0.4375	-0.8044	1.0000